FIG. 1

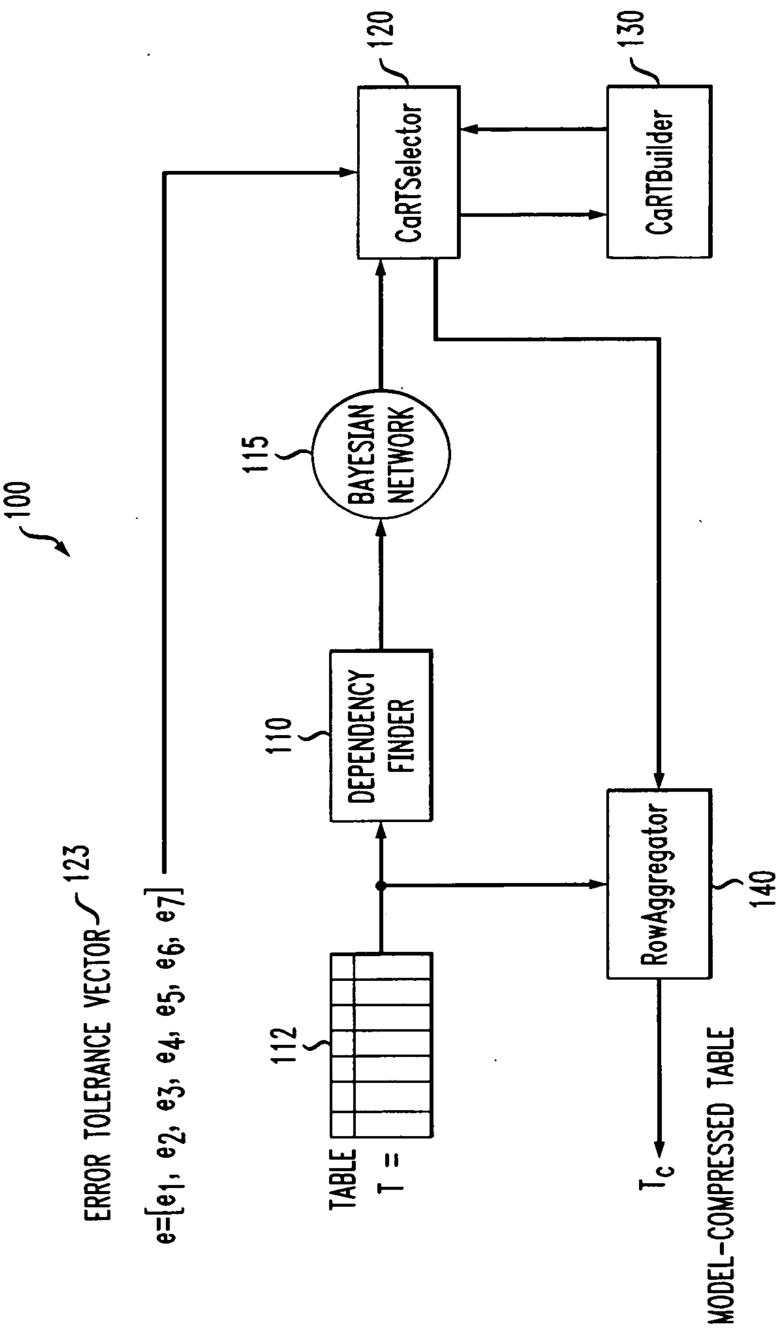

100
ERROR TOLERANCE VECTOR
123
e=[e1, e2, e3, e4, e5, e6, e7]
TABLE
T =
112
110
DEPENDENCY FINDER
115
BAYESIAN NETWORK
CaRTSelector
120
CaRTBuilder
130
RowAggregator
140
Tc
MODEL-COMPRESSED TABLE

FIG. 2

The Greedy CaRT Selection Algorithm

procedure Greedy $(T(X), \bar{e}, G, \theta)$

Input: n-attribute table T and n-vector of error tolerances $\bar{e}$; Bayesian network G on the set of attributes X and threshold θ on the relative benefit for selecting a CaRT predictor.

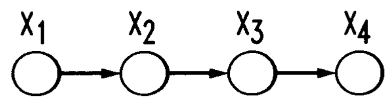
Output: A set of materialized (predicted) attributes X_{mat} ($X_{pred} = X - X_{mat}$) and a CaRT predictor for each $X_i \in X_{pred}$.

begin

1. $X_{mat} := X_{pred} := \Phi$
2. let $< X_1, X_2, \ldots, X_n >$ be the attributes in X sorted in *topological order* of G
3. for i :=1,...,n
4. if $\Pi(X_i) = \Phi$ then $X_{mat} := X_{mat} \cup \{X_i\}$ /* X_i must be materialized if it has no parents in G */
5. else
6. M := BuildCaRT $(X_{mat} \rightarrow X_i, e_i)$
7. if (MaterCost (X_i) / PredCost $(X_{mat} \rightarrow X_i) > \theta$) then $X_{pred} := X_{pred} \cup \{X_i\}$
8. else $X_{mat} := X_{mat} \cup \{X_i\}$
9. end
10. end

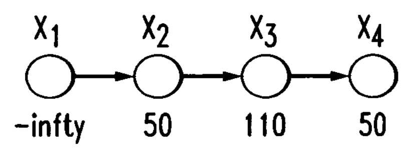
end

FIG. 3A



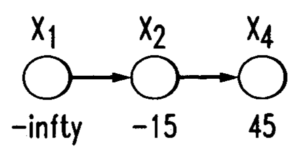
BAYESIAN NETWORK G

FIG. 3B



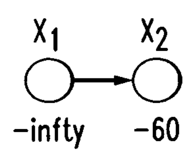
(b) Gtemp (FIRST ITERATION)

FIG. 3C



Gtemp (SECOND ITERATION)

FIG. 3D



Gtemp (THIRD ITERATION)

FIG. 4

The MaxIndependentSet CaRT Selection Algorithm

```
procedure MaxIndependentSet (T(X) , ē, G, neighborhood() )
Input:  n-attribute table T and n-vector of error tolerances ē;
        Bayesian network G on the set of attributes X and function
        neighborhood () defining the "predictive neighborhood" of a
        node X_i in G (e.g., Π (X_1) or β (X_i)).
Output: A set of materialized (predicted) attributes X_mat (X_pred = X -
        X_mat ) and a CaRT predictor PRED (X_i ) → X_i for each X_i ∈ X_pred.
begin
1.  X_mat := X,  X_pred := Φ
2.  PRED (X_i) := Φ for all X_i ∈ X, improve := true
3.  while (improve ≠ false) do
4.      for each X_i ∈ X_mat
5.          mater_neighbors (X_i) :=
            (X_mat ∩ neighborhood(X_i )) ∪ {PRED (X) : X ∈ neighborhood
            (X_i) , X ∈ X_pred }-{X_i }
6.          M := BuildCaRT (Mater_neighbors (X_i) → X_i, e_i)
7.          let PRED (X_i ) ⊆ mater_neighbors (X_i) be the set of
            predictor attributes used in M
8.          cost_change_i :=0
9.          for each X_j ∈ X_pred such that X_i ∈ PRED (X_j)
10.             NEW_PRED_i (X_j) := PRED(X_j)-{X_i} ∪PRED (X_i)
11.             M :=BuildCaRT (NEW_PRED_i (X_j) → X_j, e_j
12.             set NEW_PRED_i (X_j) to the (sub) set of
                predictor attributes used in M
13.             cost_change_i := cost_change_i + (PredCost (PRED
                (X_j) → X_j) - PredCost (NEW_PRED_i (X_j) → X_j))
14.         end
15.     end
```

FIG. 4 (cont)

build an undirected, node-weighted graph $G_{temp} = (X_{mat}, E_{temp})$ on the current set of materialized
attributes X_{mat}, where:
    (a) $E_{temp} := \{ (X,Y) : \text{for all pairs } X, Y \in X_{pred} \} \cup$
        $\{ (X_i, Y) : \text{for all } Y \in X_{mat} \}$
    (b) weight (X_i) := MaterCost (X_i) −PredCost (PRED(X_i) $\rightarrow X_i$) +cost_change$_i$ for each $X_i \in X_{mat}$
S := FindWMIS (G_{temp})   /* select (approximate) maximum weight independent set in G_{temp}
    as "maximum-benefit" subset of predicted attributes */
if ($\Sigma_{X \in S}$ weight $(X) \leq 0$) then improve := false
else/* update X_{mat}, X_{pred}, and the chosen CaRT predictors */
    for each $X_j \in X_{pred}$
        if (PRED $(X_j) \cap S = \{X_i\}$) then PRED (X_j) := NEW_PRED$_i$ (X_j)
    end
    $X_{mat} := X_{mat} - S$, $X_{pred} := X_{pred} \cup S$
end
end /* while */
end

FIG. 5

Algorithm for Estimating Lower Bound on Subtree Cost

```
procedure LowerBound (N, e_i, b)
Input:  Leaf N for which lower bound on subtree cost is to be
        computed; error tolerance e_i for attribute X_i; bound b
        on the maximum number of internal nodes in subtree
        rooted at N.
Output: Lower bound L(N) on cost of subtree rooted at N.
begin
    for i := to r
        minOut [i, 0] :=i
    for J := 1 to b + 1
        minOut [0, j] :=0
    1 :=0
    for i := 1 to r
        while x_i - x_1+1 > 2 ei
        1 :=1 = 1
     for j := 1 to b + 1
        minOut [i,j] := min {minOut[i - 1,j] + 1, minOut [1,j-1]
    end
    L(N) := ∞
    for J := 0 to b
        L(N) :=min {L(N) , 2j + 1 + j log (|X_i|) + (j + 1 + minOut
        (r, j+1)) log (|dom(X_i)|)}
    L(N) := min {L(N) , 2b + 3 + (b + 1) log (|X_i|) + (b +2) log
    (|dom(X_i) |) }
    return L (N)
end
```

FIG. 6

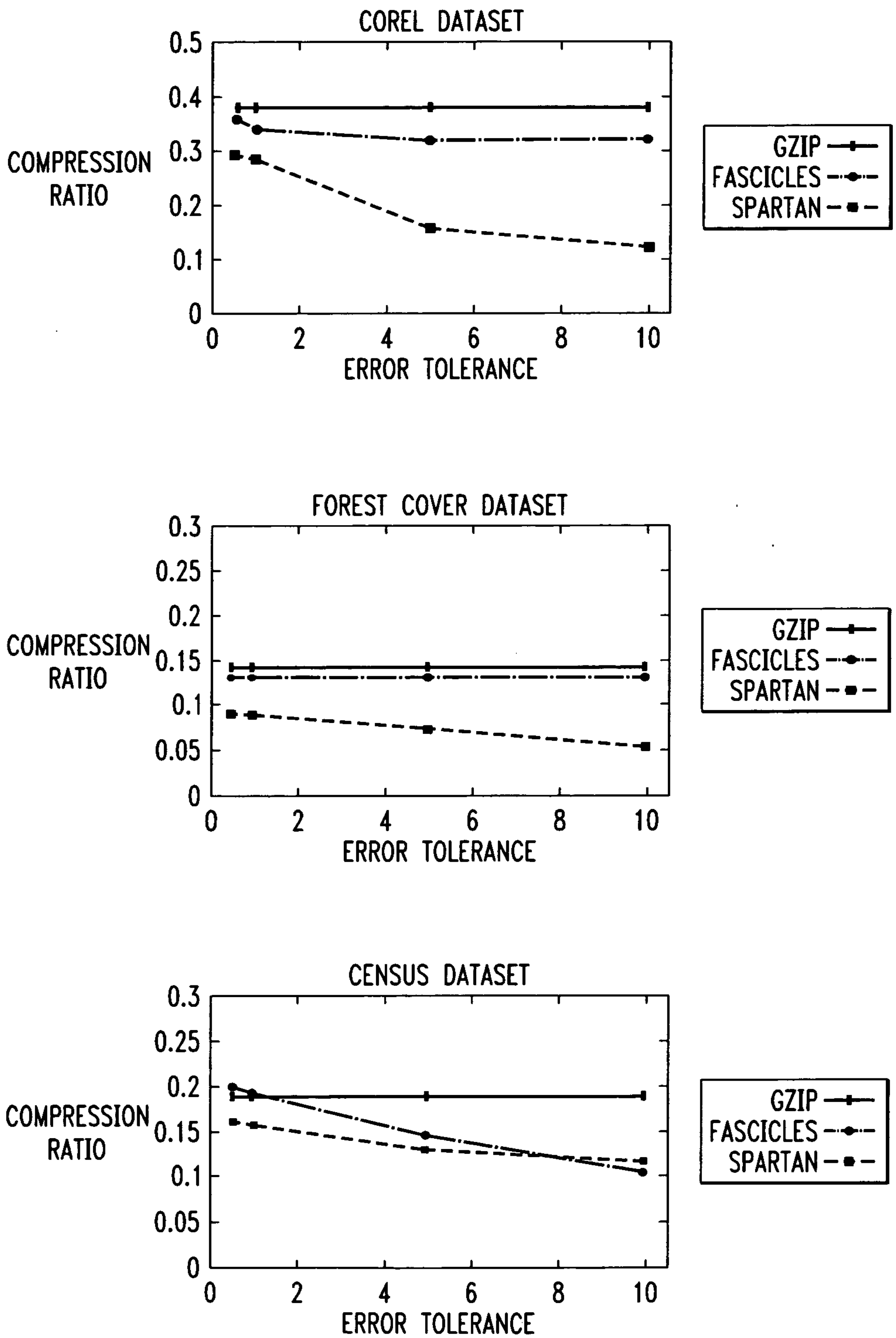

COREL DATASET
COMPRESSION RATIO
0.5
0.4
0.3
0.2
0.1
0
0
2
4
6
8
10
ERROR TOLERANCE
GZIP
FASCICLES
SPARTAN
FOREST COVER DATASET
COMPRESSION RATIO
0.3
0.25
0.2
0.15
0.1
0.05
0
0
2
4
6
8
10
ERROR TOLERANCE
GZIP
FASCICLES
SPARTAN
CENSUS DATASET
COMPRESSION RATIO
0.3
0.25
0.2
0.15
0.1
0.05
0
0
2
4
6
8
10
ERROR TOLERANCE
GZIP
FASCICLES
SPARTAN

FIG. 7A

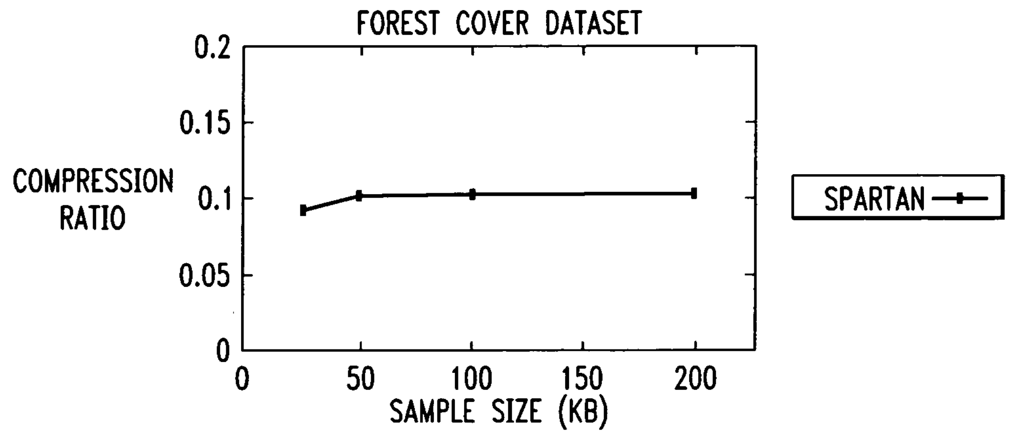


FIG. 7B

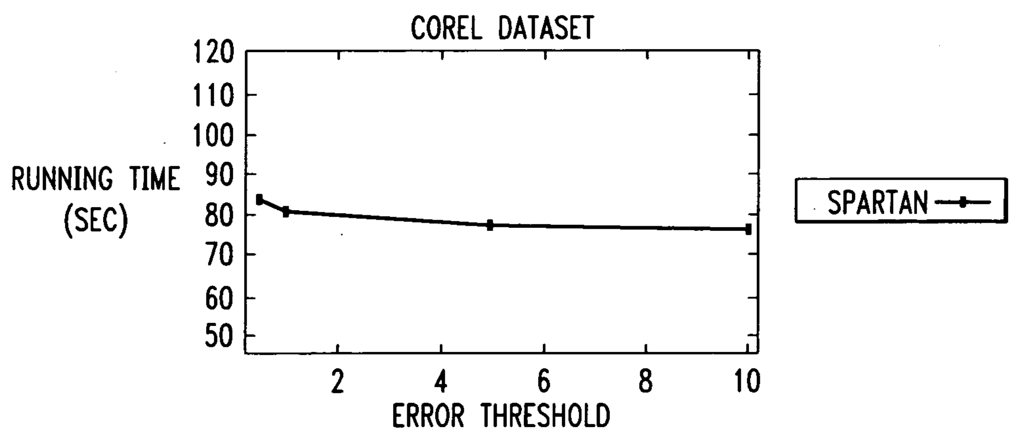


FIG. 7C